



CD-MAKE 2017

The more the merrier Federated learning from local sphere recommendations





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Introduction and Motivation





- Thinking about Machine learning from a *European* startup perspective
- Which brings a few particular challenges with it:
 - Usually less startup capital than U.S. competitors
 - => therefore less money for computing power
 - much fewer possible customers (initially) than Asian competitors
 - => less initial data
 - GDPR is a major impediment
 - => expressely prohibits use of personal data...
- Maybe we can circumnavigate all those hurdles via
 Client-side Machine Learning

Introduction and Motivation





- How far away are relevant decision points within a social networks usually?
- Leskovec, even back in 2006 observed recommender cascades within an online shopping system
 - for 3 out of 4 products: maximum size of cascade was < 10

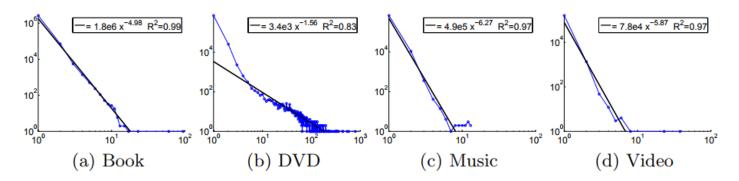


Fig. 1. Size distribution of the cascades for the four product types (log size of cascade vs. log count). Superimposed line presents a power-fit. R² is the coefficient of determination.

Leskovec, Jure, Ajit Singh, and Jon Kleinberg. "Patterns of influence in a recommendation network." Pacific-Asia Conference on Knowle dge Discovery and Data Mining. Springer, Berlin, Heidelberg, 2006.

Recommendation Cascades





- most were not chains, but one node influencing many others (spl its) or several recommendations directed at one node (merges)
- single recommendations made up the majority of 'cascades'
- overall, the average ego network from which relevant recommen dations originated was little more than 1(!)

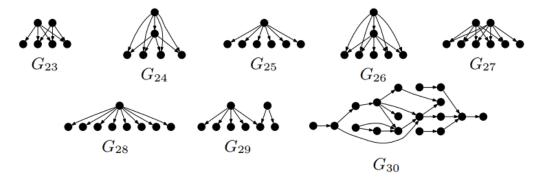


Fig. 2. Typical classes of cascades. G_{23} , G_{27} : nodes recommending to the same set of people, but not each other. G_{24} , G_{26} : one node recommends to another, and both recommend to the same community. G_{25} , G_{28} , G_{29} : a flat cascade. G_{30} is an example of a large cascade.

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Introduction and Motivation



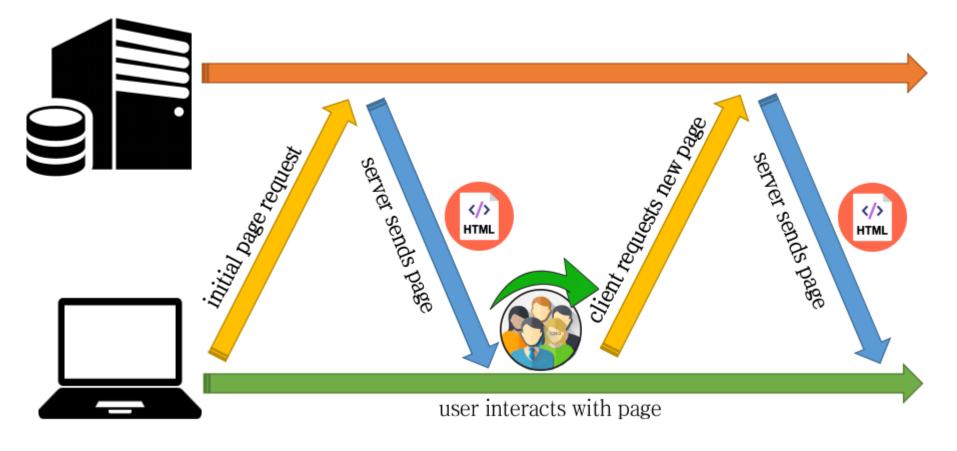


- the FB graph has been estimated to have a diameter of as low as 4
- the diameter is shrinking with new connections (despite new users)
- although the graph is globally very sparse, individual node neighborhoods contain surprisingly dense structure
- Conclusion: We dont need the whole graph to calculate good recommendations – in most cases we only need to take a node's immediate vicinity into account!





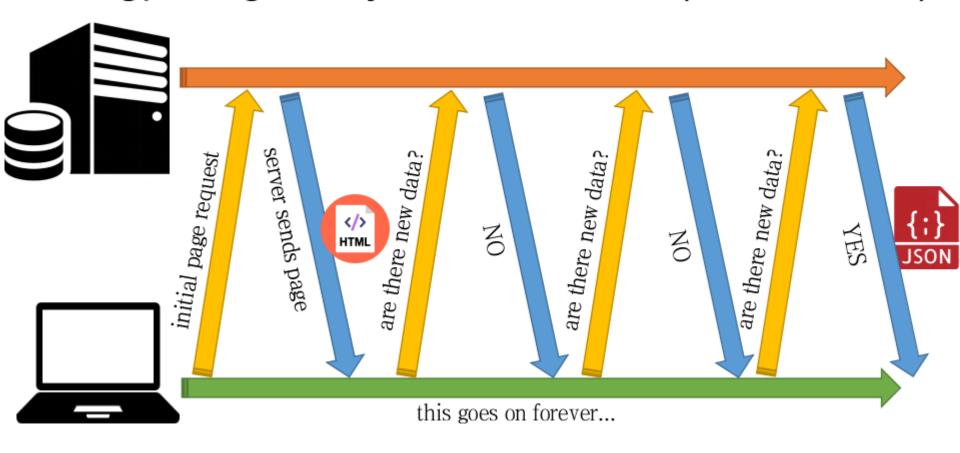
Traditional request / response model < 2005







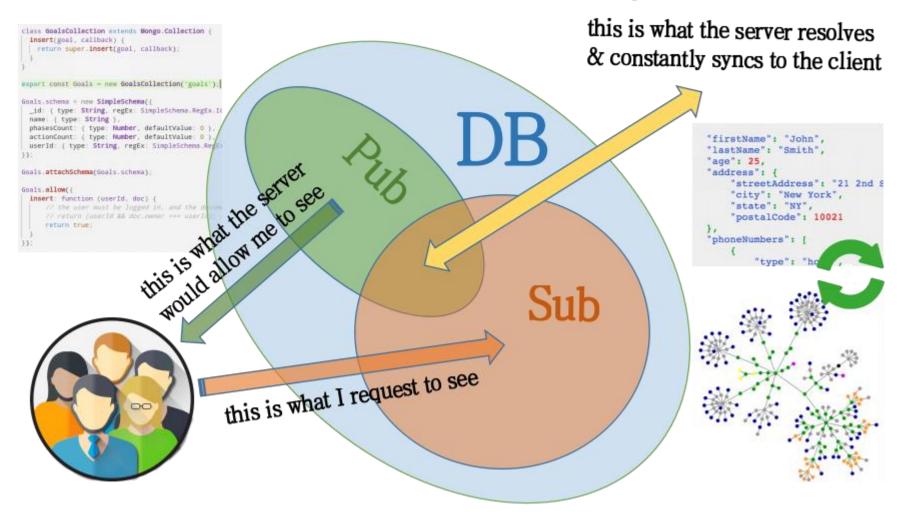
Longpolling via Ajax 2005 - 2012 (& still in use)







Modern Pub/Sub with constant synchronization



Consequences of Pub/Sub





- This means in effect, that all information within the neighborhood of a node (if you see it from a network perspective) is constantly available within the browser / mobile device
 - my direct friends on a social network
 - the information / resources within my project group
- Combining the two principles of Pub/Sub and recommender cascades, we see that a majority of relevant recommenddations could be computed directly on the client

Global sphere / Local sphere



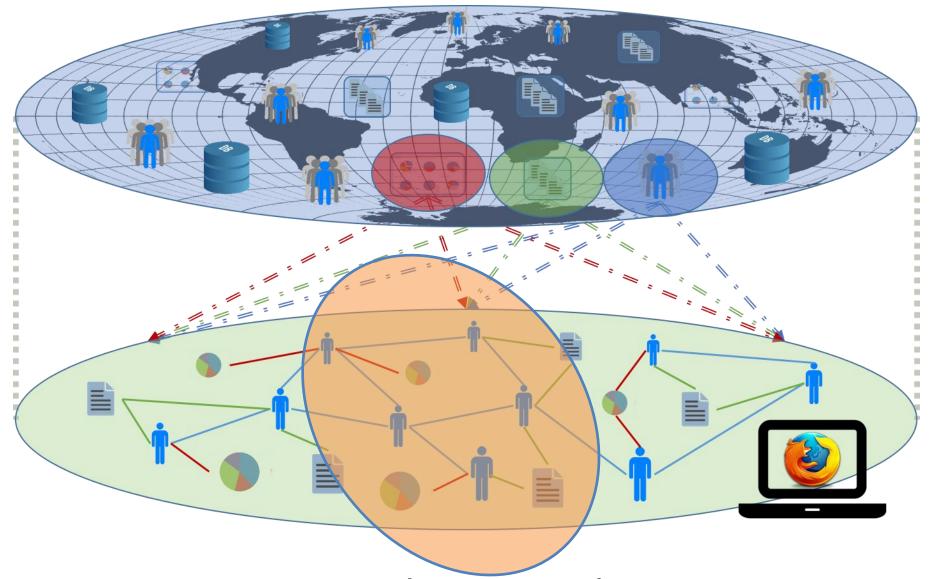


- Many globally distributed databases dont have to / cannot be implemented as a graph (facebook also does not store one central graph, but rather superimposes relational DBs with a logical graph layer - GraphQL)
 - would need too many globally propagating updates —
 "the consequences of a tiny node update could affect the farthest reaches of the global graph"
- The local sphere can get it's information from many pub/sub mechanism targeting different endpoints in the global sphere
- The local sphere is a superset of the actual user's data enriched with data from it's relevant vicinity, plus possibly sensitive information only available on the client itself.

Global Sphere / Local Sphere / User data







GraphQL / Websockets / etc.

Advantages





- GDPR says processing of personal data is expressely prohibited
 - but they are talking about data you collected
 - what if you haven't collected it because it never left the users' device?
- You can potentially use a wealth of information available on the client device you could never access server-side
 - address book
 - calendar
 - GPS
 - emails
 - messaging services
 -

Advantages (coming back to the startup idea)





- BYOPP "Bring your own processing power"
 - World's fastest supercomputer can do 93 Petaflops
 - A Geforce 1080 runs at about 12 Teraflops (single prec.)
 - You need ~7,750 customers with such cards to reach the TaihuLight
 - iPhone 7: GPU operates at 729.6 GFLOPS
 - ~130k iphones stack up to the TaihuLight
- of course apps can never access the full potential of a client device (think of battery alone...), but those numbers give a good feeling about the magnitude we're talking about
- a few hundred thousand users is not much for a successful startup today => SCALABILITY !!!

Proposed mechanism





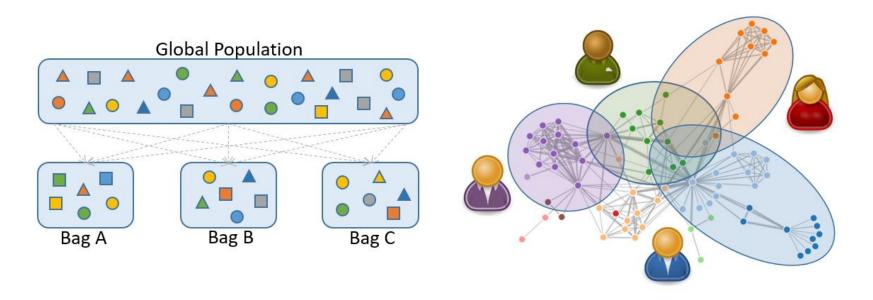
- 1. Pub/Sub keeps the local sphere in sync with global data
- 2. Local algorithms compute recommendations
 - these can also come from a client-side crawler (like the FB crawler which scans URLs you paste into a comment field and extracts images from a website)
- 3. Upon user acceptance, a new node is introduced into the local sphere + updated to the global sphere
- 4. Client devices with overlapping local spheres now receive that node in the background
- 5. Their recommenders respond... => 1...

Machine Learning / Conclusion





- Maybe it's even possible to implement Machine Learning paradigms on such a distributed platform (see bagging below)
- Eventually, we might not even have to curate a global graph anymore - it could be a virtual, implicit, query-able instantiation of the sum of all local spheres at any given point in time!









Thank you!